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Are the Central and Eastern European Transition Countries still vulnerable to a Financial Crisis? Results from a Multivariate Logit Analysis

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Abstract

The aim of the paper is to analyse the determinants of financial crises in a sample of nine transition countries in Central and Eastern Europe with a modified logit model. The modification takes explicitly into account the rare event characteristic of a currency crisis. Our results suggest that it is possible to explain the occurrence of crises with only a small number of macroeconomic variables. The variables which contribute positively to the probability of a crisis are: i) the ratio of the current account deficit to GDP; ii) the ratio of the budget deficit to GDP; iii) the change in currency reserves; iv) the amount of real appreciation of the currency relative to a trend, and v) the change in exports. Short-term debt by banks, which played a key role in the history of the Asian crises, was not an important factor in the build up of the crisis potential in Central and Eastern Europe.

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1. Introduction

The increased frequency of severe financial crises – i.e. the more or less contemporaneous occurrence of both a currency and a banking crisis – in the last years has lead to an intensified research effort into the underlying factors and causes driving the build-up of economic distress and subsequently the outbreak of a financial crises. Much of the research has centered on the emerging economies in Asia and Latin America. Important work in this area was done by the IMF, who developed a probit approach to assess the vulnerability of different countries to financial crises. This paper builds upon this work and attempts to fill the gap on the origins of crises in the emerging markets in Central and Eastern Europe. Our focus is to highlight the causes of financial crises in several of the Central and Eastern European candidate countries to the EU as well as in Turkey and Russia, two important countries of the region who have lived through severe crises recently.

At the beginning of the transformation process in the early 1990's several transformation countries introduced a fixed or predetermined exchange rate system. The exchange rate anchor provided an effective device for guiding the disinflation programmes and for the subsequent establishment of macroeconomic stability. However, inflationary persistence in the presence of a fixed – or predetermined – nominal exchange rate, resulted in a real exchange rate appreciation in several countries which was not matched equally by productivity gains. Consequently, the real appreciation led to a decline in exports' competitiveness and to sizeable current account deficits. During the period from 1996 through 2000 all countries in our sample except Russia have experienced an appreciation of the real exchange rate against the Euro. With more than 30 % it was the strongest for Latvia, Romania and Turkey. Since September 1998 the Russian rouble also appreciated by almost 25 %. The Hungarian Forint due to the crawling peg regime appreciated least, by only 13 % over the observation period.

The fixed exchange rate regimes changed the pecking order of capital inflows in favour of short-term speculative inflows (Razin/Sadka/Yuen, 1996). With the accession to the OECD, the Czech Republic (December 1995), Hungary (May 1996), Poland (July 1996), and the Slovak Republic (October 2000) had to open their capital accounts by accepting the *OECD Codes of Liberalisation of Capital Movements and Current Invisible Operations.* Although the opening of the capital account is generally beneficial as it enables a better allocation of capital, it also exposed the countries to the risk of a sudden and massive reversal of capital flows. Once a crisis happens, its resolution often requires international financial assistance. Here, the Central and Eastern European countries (henceforth CEE countries) are in an akward position: On one hand, they cannot simply turn to the IMF or other international institutions for assistance as it would hamper their chances of a rapid accession. On the other hand, the EU has no obligations whatsoever to help out non-members. As a consequence, the accession candidates have to be very careful of not running into trouble if they strive for an orderly accession.

The rest of the paper is structured as follows. The next section provides a brief survey on previous studies on the origins of currency crises. In section three the criterion for distinguishing crisis periods from tranquil periods is presented. Sections four and five outline the estimation method and provide a description of the explanatory variables. The empirical results are presented in section six, which is followed by an analysis of the forecasting performance of the model. The usefulness of the logit model as an early warning system for crises is examined in section eight. The final section draws some conclusions and outlines a few policy options for the transition countries in the wake of accession to the European Union.

2. Survey of the Literature

Numerous currency crises in the second half of 1990s have stimulated economic research into the origins of these crises. The economic theory on the causes of currency crises can be devided into three generations of models – named according to the chronological development of the theory.

In the first-generation models (Krugman, 1979) a currency crisis occurs due to economic policies which are inconsistent with the fixed exchange rate. In Krugman's seminal paper the driving force is an expansionary monetary policy which is rooted in the monetisation of a fiscal deficit. With unchanged money demand this necessarily results in inflationary pressure. The subsequent real appreciation leads to a current account deficit and diminishing reserves. Ultimately, the abandoning of the peg is inevitable.

The second-generation models originate in the work of Flood/Garber (1984) and Obstfeld (1986). Central to these models is the element of self-fullfilling expectations and the existence of multiple equilibria. A currency can be subject to speculative attacks even if the macroeconomic fundmentals appear to be sound. In case of a speculative attack a country raises the interest rate to defend the fixed exchange rate. But the ensuing costs, for instance, in terms of foregone growth or higher unemployment, may outweigh the advantages of maintaining the fixed exchange rate. Thus, it is optimal for the country to abandon the peg.

Third-generation models emphasise the interaction between a banking crisis and a currency crisis (Kaminsky/Reinhart, 1996; Kaminsky, 1998). The key variables responsible for the interaction are excessive short term debt and domestic credit by banks which reflect the overlending and overborrowing behaviour of banks (McKinnon/Pill, 1997). This is often accompanied by a currency and maturity mismatch. The causal relationship between a banking and a currency crisis can run both ways, but in practice a banking crisis is more often preceded by a currency crisis than the other way round. Large open foreign exchange positions on behalf of the banks leave them vulnerable to currency depreciations. If the depreciation is large enough the bank's liabilities can easily exceed the assets and force the bank into bankruptcy.

On the empirical research side on currency crises two different strands have emerged: The first goes back Kaminsky/Reinhart (1996). Its basic idea is to find some sort of anomolous behaviour in the time series of various macroeconomic variables prior to the outbreak of a crisis. By defining a threshold for each of the reviewed variables, it is possible to distinguish between a normal and a signaling behaviour of a variable. The number of signals can be summarised in a composite indicator and the level of the indicator then determines the level of vulnerability of a country for a crisis. Examples of this type of model include Kaminsky/Lizondo/Reinhart (1998) and Goldstein/Kaminsky/Reinhart (2000).

The second strand of research tries to capture the causes of crises in terms of probability by using a logit or probit type of model. One of the first studies in this field was done by Eichengreen/Rose/Wyplosz (1996) who used data from 1959 through 1993 for industrial countries to characterize common causes of many currency crises. The analysis by Frankel/Rose (1996) was motivated by the Mexico crisis in 1994. They examine a panel of 105 developing countries from 1971 through 1992, while Radelet/Sachs (1998) undertook a cross-country analysis of 20 countries for the year 1995 to examine how strongly these countries were affected by the Mexico crisis. The probit type model plays an important role in country risk analysis of the IMF as well. A detailed description of the IMF's *Developing Country Studies Division Model* (DCSD) can be found in Berg et al. (1999) and Berg/Patillo (1999a,b,c).

Common to both strands of research is the finding that falling foreign exchange reserves and an appreciation of the real exchange rate precipate most financial crises and are therefore good indicators for upcoming speculative attacks.

3. Periods of Speculative Pressure

In order to identify the variables and factors responsible for a build up of a certain vulnerability potential, it is necessary to distinguish crisis periods from tranquil periods. An useful and widely used instrument to determine crisis periods is the Exchange Market Pressure index (henceforth EMP index) suggested by Eichengreen/Rose/Wyplosz (1996, henceforth ERW). The EMP index represents the weighted sum of changes in the nominal exchange rate, the short-term interest rate, and the currency reserves. The basic idea of the index is that a period of speculative pressure - or synonymously a crisis - is called as soon as the index crosses a certain threshold. This reflects the fact that a central bank has generally the option to defend the own currency by selling foreign reserves or by raising interest rates or a combination of the two measures. The main advantage of the index is that it manages to incorporate unsuccessful speculative attacks.

To take into account economic circumstances, the changes in the variables are measured relative to a reference country. For our purposes Germany (denoted with the subscript G) is chosen as the reference country as it is by far the largest single trading partner for the CEE countries (except for Turkey). Since most of the trade is factorised in Euro the nominal exchange rate is consequently defined vis-à-vis the Euro. The EMP index of country i is formally defined as:

$$EMP_{i,t} = \alpha \triangle e_{i,t} - \beta \triangle (r_{i,t} - r_{G,t}) + \gamma \triangle (i_{i,t} - i_{G,t}), \tag{1}$$

with $e_{i,t}$ being the nominal exchange rate vis-à-vis the Euro; $r_{i,t}$ the ratio of currency reserves to GDP, i_i the short term interest rate, and t being the time index. The parameters α, β, and γ are the weights of the three policy options and sum up to unity. In addition, the three variables (exchange rate, reserves, and interest rate) are normalised by their variance to take account of possible volatility shifts. For simplicity reasons the parameters - α, β, γ - are weighted equally.[1]

After having calculated the EMP index for each country it is possible to distinguish between crisis and tranquil periods. If the index crosses a certain threshold the corresponding month is declared a crisis month. Here we follow ERW (1996) and call a crisis if the index deviates by more than one and half standard deviations from its mean, i.e.

$$y_{i,t} = \begin{cases} 0 & \quad \quad otherwise \\ 1 & if \quad EMP_{i,t} \geq \mu_{EMP_i} + 1.5\sigma_{EMP_i} \end{cases} \tag{2}$$

where μ_{EMP} and σ_{EMP} denote the sample mean and the standard deviation of the EMP index, respectively.

[1] Different weighting schemes such as 50%, 30%, 20% did not yield substantially different results compared to the one applied (33%, 33%, 33%).

The EMP index does not always coincide with periods of currency realignments. In case of the Czech currency crisis in May 1997 and the Russian crisis in August 1998 the index signals speculative pressure only few months after the abandoning of the exchange rate peg (see Figure 1). To account for the slow adjustment behaviour, the index is led by six months.

Usually, a financial crisis is a sudden event, although the pressure culminating in such an event may build up over months. In order to reflect this behaviour adequately in our estimation, we define a crisis period in the following way: As soon as the EMP index crosses the threshold the corresponding month is declared a crisis month as well as the eleven months prior to this event.

4. Estimation Methodology and Data

4.1. Logit Analysis

Economic theory and historical experience indicates that the occurrence of a crisis can be explained by a number of factors, such as the current account deficit, the budget deficit, an overvalued exchange rate and other variables. Formally, the relationship between the crisis-triggering factors and a crisis can be expressed as follows:

$$\Pr(crisis_{i,t}) = \pi_i(y_{i,t} = 1 \mid \mathbf{X}_t, \beta_t) = F(\mathbf{X}_t, \beta_t) \tag{3}$$

where X_t is a set of explanatory variables and β_t is a vector of parameters to be estimated. Specifically, we assume for the estimation a cumulative logistic distribution function as the functional form for the relationship between the explanatory variables and the probability of the outbreak of a crisis, i.e.

$$\pi_i(y_{i,t}) = \frac{1}{1 + e^{-\beta' \mathbf{X}_{i,t}}} \ , \tag{4}$$

where y_i is a dichotomous variable as defined in equation (2).

King/Zeng (2001a, 2001b) have shown that with such a set up the probability of the crisis event, $[P(Y = 1)]$, in a logistic regression is underestimated and hence, the probability of the non-event, $[P(Y = 0)]$, is overestimated. Therefore, this so-called *rare event bias* has to be corrected. Its main idea is briefly sketched in the next section.[2]

[2] An elaborated description of the bias, the correction, and the proofs can be found in King/Zeng (2001b).

4.2. Rare Event Bias

A financial crisis - like an earthquake - happens very rarely, it is therefore justified to characterise such a phenomenon as a *rare event.* This means in terms of estimating a model with a limited dependent variable that while there are numerous *tranquil* periods (or zeros) *crisis* periods are quite seldom (or ones in the binary case). In general, the estimate of β in equation (4), $\widetilde{\beta}$, is biased in finite samples and this bias may be amplified by rare events.

The bias correction is done in two steps. In a first step the finite sample bias is approximated. For the special case with a constant term and just one explanatory variable which is set to 1, the bias in the estimated constant term $\widehat{\beta}_0$, can then be approximated as

$$E(\widehat{\beta}_0 - \beta_0) \approx \frac{\overline{\pi} - 0.5}{n\overline{\pi}(1-\overline{\pi})} \ , \tag{5}$$

where $\overline{\pi} = (1/n)\sum_{i=1}^{n} \pi_i$ and where it is assumed that a rare event has a probability of less than .5. Since the numerator is negative the entire bias term is negative. Therefore, the estimate $\widehat{\beta}_0$ is too small and as a consequence, $\Pr(Y = 1)$ is underestimated.

In a second step the probability calculations are adjusted for the sampling error of the less biased estimate $\widetilde{\beta}$. The probability can be calculated with the less biased $\widetilde{\beta}$ as:

$$\widetilde{\pi}_0 = \Pr(Y_0 = 1 \mid \beta_0) = \frac{1}{1 + e^{-\widetilde{\beta}\mathbf{x}_0}} \ . \tag{6}$$

However, this still ignores the fact that $\widetilde{\beta}$ is estimated rather than known. Intuitively, taking into account the uncertainty about β results in a distribution with a greater variance. Although the mean of the distribution stays the same, $\mu = x_i\widetilde{\beta}$, whether ignoring the uncertainty about β or not, the size under the distribution increases for the same threshold. Hence the 'true' probability of the rare event involves a corrections factor, C_i:

$$\Pr(Y_i = 1) \approx \widetilde{\pi}_i + C_i \tag{7}$$

with the correction factor

$$C_i = (0.5 - \widetilde{\pi}_i)\widetilde{\pi}_i(1 - \widetilde{\pi}_i)\mathbf{x}_0 V(\widetilde{\beta})\mathbf{x}_0' \tag{8}$$

where V is the variance-covariance matrix. The intuition behind the correction is quite simple; if $\widetilde{\beta}$ would be known C_i would become zero and conversely, the larger the uncertainty about $\widetilde{\beta}$, the larger the correction factor.[3]

4.3. Data

The multivariate rare event logit (henceforth RE logit) estimation is done for nine countries. The sample comprises: Bulgaria, Romania, Hungary, Latvia, Lithuania, Poland, Russia, Slovenia, and Turkey. For the out-of-sample estimation three countries are used: Croatia, Estonia, and Slovakia. The sample period runs from January 1996 through December 2001 with at most 108 observations for each country. During this period five episodes of financial crises occurred, namely: in Bulgaria in January 1997, in the Czech Republic in May 1997, in Russia in August 1998, in Romania in February 1999, and in Turkey in November 2000.

The data for most countries are taken from the database of the Vienna Institute for International Economic Studies (WIIW). Data for the Baltic countries and Turkey are gathered from the national statistical offices and national Central Banks. The data on foreign debt and capital flight are taken from the Bank for International Settlements (BIS). Since data for GDP and the current account balance are only available on a quarterly basis, the monthly data are generated through linear interpolation. The sovereign credit ratings are readily available from Standard & Poor's. The election data are obtained from the International Foundation for Election Systems (IFES). The real exchange rates of the national currencies vis-à-vis the Euro are calculated using the Harmonised Consumer Price Index (HVPI), which is obtained from Eurostat. All calculations were done with Stata 7.0.

5. List of Explanatory Variables

The tested variables comprise a wide range of macroeconomic and financial variables. The choice of possible explanatory variables is based on considerations of the theoretical and empirical literature on currency and banking crises, concentrating on those variables that are available on a timely basis. The variables can be broadly split into three groups. The first group relates to variables that are trying to capture the degree of distress in an economy. These variables are associated with the first and second generation of crisis models and comprise mainly macroeconomic variables. The second group of variables relates to the banking sector. These variables should reflect the size of the banking market and its vulnerability to a devaluation giving rise to a *twin crisis* phenomenon (Kaminsky/Reinhart, 1996). The third group includes the sovereign credit rating and an election dummy which tries to capture the

[3] The programme code for the bias correction is implemented as an ADO-file in Stata and can be downloaded from the internet [`http://gking.harvard.edu/files/relogit.zip`].

phenomenon that the outbreak of a looming crisis is postponed until after the election while the credit rating as a reflection of market sentiment to a sovereign default indicates the risk of a sudden reversal of capital inflows. The list of explanatory variables is as follows:

Growth rate of GDP. Currency crises are often preceded by a recession. In general, an economy is more vulnerable to a crisis when economic growth slows down (Hardy/Pazarbasioglu, 1998).

Ratio of the Budget Balance to GDP. This indicator corresponds to the classic Krugman-type explanation for a currency crisis. A large budget deficit is a typical source of a country's vulnerability for a crisis and signals an unsustainable economic policy. A steady rise of the budget deficit can be expected before the eruption of a crisis as the higher deficit will impair the government's willingness to service its debt (Krugman, 1979).

Ratio of the Current Account Balance to GDP. Although emerging market economies can be expected to experience some persistent productivity growth and terms-of-trade improvements because of the Balassa-Samuelson-effect it may not be sufficient to finance a rising current account deficit for a longer period of time. Ultimately, the current account deficit may become to be judged unsustainable by the market participants (Corsetti/Pesenti/Roubini, 1998).

Growth rate of Exports. Reduced exports inhibit a country's ability to earn foreign exchange to finance an existing current account deficit. Thus, diminishing exports add to the crisis potential. Additionally, this variable indicates decreasing competitiveness and possible problems of domestic enterprises (Radelet/Sachs, 1998).

Growth rate of Currency Reserves. Diminishing currency reserves limit a country's ability to defend its currency, making a devaluation of the currency or the abandoning of the peg in case of a speculative attack more likely. Conversely, the higher a country's international liquidity, the better the cushion to defend a speculative attack against the currency (Feldstein, 1999).

Overvaluation of the Real Exchange Rate. Usually, a currency crisis is closely linked to an overvalued real exchange rate. A persistently overvalued currency has adverse effects on exports, growth prospects, and ultimately, a country's ability to service its debt. The variable is defined as the negative deviation of the real exchange rate from the long term linear trend (Kaminsky/Lizondo/Reinhart, 1998).

Growth Rate of Portfolio Investment Inflows. Portfolio investment inflows (PI) can easily be liquidated if market sentiment changes and thus, are more easily reversed than long-term flows. A current account deficit that is financed by extensive PI is therefore less sustainable than a deficit financed by FDI. Hence, large PI inflows if not balanced by sound macroeconomic policy may lay the ground for future problems.

World Interest Rate. A rise in the interest rate abroad may tilt the yield against investment in emerging market country This can induce a sharp and massive reversal of PI flows. In addition, if a country has accumulated a substantial amount of foreign debt higher interest payments as a consequence of the interest rate hike will put additional burden on the budget (Kaminsky/Lizondo/Reinhart, 1998).

Ratio of the Bank Deposits to GDP. When a banking crisis is looming, domestic residents, who are usually better informed than foreigners, slowly loose faith in the stability of the banking sector and begin to withdraw their savings. Thus, a drop in bank deposits can be expected before a crisis (Demirgüc-Kunt/Detragiache, 1999).

Growth Rate of Domestic Credit. In the time leading up to a crisis a rapid credit expansion can usually be observed. The main reason for this stylised fact lies in lending booms that typically follow financial deregulation and the dismantling of capital controls. This may create balance sheet problems for the banks in form of non-performing loans (Mishkin, 1997).

Ratio of Short-term Foreign Debt to Currency Reserves. Following financial liberalisation, massive inflows of foreign capital can create macroeconomic imbalances that ultimately prove unsustainable. The opening of the capital account creates incentives for domestic banks which are characterised as an 'over-borrowing syndrome', whereby the riskiness of borrowing from abroad to finance the current account deficit is systematically underestimated by the banks (McKinnon/Pill, 1997).

Growth Rate of Capital Flight. Domestic residents have usually an information advantage over foreigners about domestic policy issues. The protection of assets against a sudden and drastic drop in value in course of a crisis is - besides tax evasion - a main motivation to shift assets abroad.

Credit Rating. Sovereign credit ratings play an important role in determining the terms and conditions with which a country can borrow on the international capital markets. In this sense sovereign credit ratings are often interpreted as an indicator capturing the likelihood of a country's default (Kaminsky/Lizondo/Reinhart, 1998).

Presidential/Parliamentary Elections. Quite often the timing of a crisis is closely linked to the event of a Presidential or Parliamentary election. With a nationwide election coming up, the incumbant government has strong incentives to surpress the outbreak of a crisis as it would reduce their chances of getting re-elected. This hypothesis was advocated by Dornbusch (2001) based on the experience of some Latin American countries. A necessary corrective devaluation will be postponed. In the end, the crisis happens shortly after the election, not before. In order to take this phenomenon into account a 1 is assigned for the twelve months following an election, otherwise it is 0.

6. Empirical Results

The candidate explanatory variables are successively eliminated by applying a general-to-specific model selection methodology keeping all variables that are significant at the 5% level. The results of the estimated logit models are presented in Table 2.

The resulting RE logit model comprises five variables: the current account to GDP ratio, the deviations of the real exchange rate from its trend, the budget balance to GDP ratio, the change in currency reserves, and the change in exports. The signs of all coefficients coincide with what we generally expect from economic theory. The probability of a crisis increases when exports are declining, currency reserves are falling, the real exchange rate is overvalued relative to its long term trend, and the current account and budget deficit is rising relative to GDP. The current account to GDP ratio has the largest statistical impact on the probability of a crisis. An increase in the deficit ratio by 1 percentage point would result in a 0.24 unit increase in the log of the odds ratio, while keeping the other variables at their means.

Overall, the estimated coefficients from the rare event specification of the logit model are very similar to the ones obtained from the ordinary logit model. However, there is one important exception. In the ordinary logit model *exports* are only significant at the 12 percent level whereas in the RE logit model the coefficient for *exports* has a considerably smaller variance. Thus, without correcting for the rare event characteristic of financial crises exports would have been dropped from the model, leaving out possible important information about a country's financial vulnerability.

Other than the five variables, none were found to be systematically significant. Although some of the variables had predictive power when tested alone, their statistical significance was lost when used in combination with the other explanatory variables. Moreover, the construction of interaction terms between the real exchange rate and the current account to GDP ratio and between the real exchange rate and the budget deficit were not found to be statistically significant. We tested the robustness of our results by defining variables differently and by including contemporaneous and lagged variables. None of them altered the results in a significant way.

Two results stand out among the dropped variables: First, we fail to find evidence for the hypothesis that sovereign ratings anticipate banking and currency crises. This result is consistent with the findings of Goldstein/Kaminsky/Reinhart (2000) for the Asian crises in Summer 1997. If credit ratings are interpreted as a reflection of market expectations on a country's default probability then most crises came indeed as a surprise to market participants. In this sense, the international debt markets do not provide much advance warning of a looming crisis. And second, Dornbusch's hypothesis (Dornbusch, 2001) that parliamentary elections play an important role in the timing of a crisis has to be rejected for the Central and East European countries. No evidence is found that an incumbant government tries to subdue tensions in the foreign exchange markets until after the elections.

7. Forecasting Performance

In order to assess the forecasting performance of the model we considered various goodness-of-fit measures. The model was tested both in-sample as well as out-of-sample.

7.1. Goodness of Fit Measures

The basic idea of the performance tests is to compare the probability estimates with the actual outcomes, as measured by the dichotomous (zero-one) variable (Diebold/Lopez, 1996). Let P_t be the time series of probability estimates, where P_t is the probability of a crisis at time t and calculated from the estimated odds-ratio of the RE logit model. Furthermore, let R_t denote the time series of realisations, where R_t equals one for the interval $[t-12, t]$ if the EMP index crosses its critical threshold at time t and equals zero otherwise. The probabilities are computed for $t = 1, ..., T$ such that there are T values available for P_t and R_t.

The most common tests to evaluate the closeness of the predicted probability and the observed realisations are the following:

1. *Quadratic Probability Score (QPS).* The QPS is defined as:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2. \tag{9}$$

A QPS test statistic with a score of 0 indicates perfect accuracy.

2. *Log Probability Score (LPS).* The LPS is given by:

$$LPS = -\frac{1}{T}\sum_{t=1}^{T}\left[(1-R_t)\ln(1-P_t) + R_t\ln(P_t)\right]. \tag{10}$$

The LPS test statistic ranges from 0 to infinity, with 0 corresponding to perfect accuracy. The LPS differs from the QPS test that larger errors are penalised more heavily under LPS than under QPS.

3. *Global Squared Bias (GSB).* The GSB measures forecast calibration. It compares the average predicted probability with the average realisation and is calculated as

$$GSB = 2(\overline{P}_t - \overline{R}_t)^2, \tag{11}$$

with $\overline{P}_t = 1/T\sum_{t=i}^{T} P_i$ and $\overline{R}_t = 1/T\sum_{t=i}^{T} R_i$. The GSB lies between 0 and 2. Again, a 0 indicates a perfect match.

7.2. In-sample Performance

To assess the forecasting performance we follow Berg/Patillo (1999) and compare the predicted probabilities with some cutoff probability above which a crisis is called. Table 3 presents the results for a cutoff probability of 10 % and 20 %. The model correctly calls about 80 % of the observations at the 20 % level. This is based almost entirely on the correct prediction of the tranquil periods. These are periods which are not followed by a crisis within 12 months. The majority of crisis periods are missed at the 20 % threshold (57 %), although the model does better at the 10 % threshold when only 43 % of the crisis periods are misclassified. Despite the fact that only few crisis months are correctly anticipated, about two third of alarms are false, i.e. there is a signal but no crisis occurs within the next 12 months.

In addition, we employ a χ^2 test of independence to check if there is a systematic relationship between the forecasts and the realisations. The null hypothesis assumes that the forecasts for a binary event (in this case *crisis* and *tranquil* periods) are independent from the actual outcomes. The results of the χ^2 test show that the null hypothesis is strongly rejected for a broad range of thresholds both in-sample and out-of-sample (see Table 4). Therefore, assessments of a country's crisis vulnerability, which are based upon the RE logit model, are statistically superior to random forecasts. This result holds for a wide range of the threshold of the conditional probability. Only if the threshold is set very low, i.e. below 0.04, is the null hypothesis rejected. The results are confirmed by a comparison of the conditional and unconditional probability of a crisis. A forecast of a crisis, which is based upon the RE logit model and calls a crisis if the estimated probability is above a certain threshold, i.e. $\Pr[crisis \mid alarm]$, is correct in 31 % of all cases, whereas the chances of being correct with a pure guess, i.e. $\Pr[crisis]$, is just 13 %.

The conditional probability of a crisis depends on the threshold level. Obviously, the higher the threshold before an alarm is issued the higher will be the probability of a Type I error because more and more actual crisis periods will be missed. And consequently, the higher the threshold the lower will be the probability of a Type II error. This follows from the fact that with a rising threshold the number of correctly recognised tranquil periods increases. Figure 3 depicts the relationship between committing either a Type I or a Type II error on one hand and the cutoff probability on the other hand. The errors are calculated for the in-sample estimation. The graph shows how the error probabilities change when the threshold varies. The two functions intersect at a threshold value of about 12 % which corresponds to a probability of error of 32 %.

7.3. Out-of-sample Performance

To do out-of-sample tests we use the estimated coefficients, $\widehat{\beta}$, of the RE logit regression as reported in Table 2 together with the same explanatory variables, $\mathbf{X}_{i,t}$, to generate the predicted probabilities. These values can be interpreted as true probability forecasts for countries not included in the original sample. The out-of-sample probability calculations are done for Estonia, Croatia, and Slovenia. However, a caveat applies here: although the countries are not included in the original sample, all three countries belong to the same region as the in-sample countries. Thus, it was very likely that these countries experienced some contagion effects of the crises in the Czech Republic in May 1997 and in Russia in August 1998 with the consequence that the forecasting performance is better than for truly unaffected countries.

The out-of-sample results are shown in Table 3. As far as the prediction of the timing of a crisis is concerned the RE logit model does partially better out-of-sample then it did in-sample. Almost 90 % of all crisis period predictions are actually followed by a crisis at the 10 % threshold but barely half of all observations are correctly called. The QPS and the LPS also indicate a better fit out-of-sample than in-sample while for the calibration measure (GSB) the reverse is true.

8. Selecting the Optimal Threshold

After having estimated the probabilities of a crisis for various countries (see Figure 2) the crucial question is what probability is high enough for policy makers to be concerned about? This section presents a simple framework that allows to determine the optimal threshold.

8.1. The Loss Function of the Policy Maker

To illustrate the decision problem for the policy maker it is useful to begin with an example. Let us assume the following cost matrix for the policy maker:

Table 1: Cost Matrix for the Policy Maker

	alarm	no alarm
crisis	500	1000
no crisis	100	0

The matrix shows the cost for the policy maker for each of the four possible scenarios. The costs in each scenario, which are expressed in units, are assumed to be fix and known in advance to him. Each time there is an alarm the policy maker takes precautionary measures which are costly. Higher minimum reserve requirements for banks, for instance, will likely induce banks to reduce their lendings. Tighter fiscal and monetary policy will in the short run result in an increase in the interest rate thereby supporting the currency but also at the expense of crowding out capital investment. If there is a crisis, despite having taken proper actions, the damage will be limited but exceeds the cost of the no-crisis scenario. However, if a crisis happens out of the blue - hitting the policy maker unprepared - the costs incurred are the highest. Of course, a necessary condition for an early warning system to be useful is that it reduces the cost of a crisis substantially if appropriate actions are taken. In our example the cost are cut by half if timely actions are taken. If there are no alarms which are always followed by tranquil periods we are in the best of all worlds.

To determine the optimal cutoff probability we are following Demirgüc-Kunt/Detragiache (2000) and assume a simple loss function for the policy maker which is set up according to our example:

$$L = c_1(1-\omega)T_2(\tau) + c_2\omega(1-T_1(\tau)) + c_3\omega T_1(\tau), \tag{12}$$

where ω is the unconditional probability of a crisis, and c_i are the cost assigned to each scenario with $c_1 < c_2 < c_3$. T_1 and T_2 are Type I and Type II errors, respectively, and are derived from the in-sample estimation. Both types of errors depend on the threshold τ. The unconditional probability of an in-sample crisis, ω, is equal to 0.129. The loss function is the probability weighted sum of the loss if the government takes preventive measures in vain (c_1), the loss if the crisis hits the government prepared (c_2), and the loss if a crisis strikes the government completely at a surprise (c_3). If the costs are expressed in terms of the cost in the first scenario and c_1 is normalised to unity the loss function simplifies to

$$L = (1-\omega)T_2(\tau) + \gamma_1\omega(1-T_1(\tau)) + \gamma_2\omega T_1(\tau), \tag{13}$$

with the weights γ_i such that $\gamma_2 > \gamma_1 > 1$. The linear loss function assumes a risk neutral policy maker. However, this applies only if the weights, i.e. the costs, are known in advance. As soon as the policy maker can attach his own cost estimates to the different scenarios he might no longer be risk neutral despite having a linear loss function where second and higher moments do not matter.

The optimal threshold for issuing warning signals will depend on two factors: First, the unconditional probability of a crisis and second, the relative cost of an unexpected crisis. The relative cost are simply the difference of the cost incurred in the worst case secenario and the cost of the base line scenario. To determine the relationship between the threshold and the influencing factors analytically total derivatives of the loss function are taken. Implicit differentiation of equation (13) yields

$$\left.\frac{d\tau}{d\omega}\right|_{dL} = -\frac{\partial L/\partial\omega}{\partial L/\partial\tau} < 0 \tag{14}$$

Clearly, the lower the probability of a crisis, the lower will be the probability of committing a Type I error (and vice versa). By the same token, the rarer the event of a crisis becomes the higher can be the threshold to call a crisis.[4]

The total derivative w.r.t. to the relative cost of a crisis is negative for reasonable values of T_1 and T_2, which is

$$\left.\frac{d\tau}{d\gamma_2}\right|_{dL} = -\frac{\partial L/\partial\gamma_2}{\partial L/\partial\tau} < 0 \tag{15}$$

This confirms economic intuition: As the damage of an unexpected crisis is growing it becomes more worth while taking preventive measures. These measures are initiated in

[4] For the derivation of the results see the Appendix.

accordance with a falling threshold. Since Type I errors are becoming more expensive the objective of the policy maker is to avoid them at reasonable costs.

For illustration purposes, the loss function is calculated for a specific configuration of the cost parameters. The parameter c_1 of the base scenario is normalised to 1 and the parameter γ_1 of the prepared-crisis scenario is set to 2 while the cost in case of an unexpected crisis are varying (γ_2). Figure 4 shows the cutoff probability as a function of the cost in the worst case scenario. The function depicts all combinations of the cost parameters for which the loss function is minimised. Obviously, there is an inverse relationship between the opportunity or need to call a crisis and the cost of failing to anticipate a crisis. When the cost of missing a crisis are 3 times the cost of taking preventive actions an alarm is issued when the predicted probability of a crisis exceeds 26 %. However when a Type I error is more costly, say 10 times the cost of the base scenario, a crisis is already called when the predicted probability reaches 6 %.

9. Conclusions

In this paper we tested a wide range of variables, which have previously been found significant for the outbreak of crises in Asian and Latin American countries. The aim was to see whether they also prove to be influential in causing financial crises in Central and Eastern Europe. To do this, we used a modified multivariate logit model which explicitly took into account the rare event characteristic of a financial crisis.

Overall, our results support the strong empirical evidence in the literature that explains financial crises by focusing on the behaviour of a small number of macroeconomic variables. Speculative attacks tend to occur when the current account and fiscal deficits are high, when international reserves are low, when the real exchange rate has been overvalued, and when export growth is slowing down. No evidence was found for the important role played by short-term foreign debt taken up by commercial banks in the build up of the crisis potential. This feature seems to have been special to the Asian countries. Except for these factors, the other determinants of a crisis in the CEE countries are similar to the driving forces for crises in Asian and Latin America. In this respect, the CEE transition are akin to other emerging markets. In sum, the analysis provides strong empirical support for the first generation models in explaining the financial crises in Central and Eastern Europe in the second half of the 1990's. The results of the RE logit model can also be used as an early warning system for financial crises. The model has good prognostic quality rendering it better than pure guesses.

As far as recommendations for economic policy based on our empirical findings are concerned our suggestions are threefold: First, the persistent current account deficits of the transition countries while keeping in mind that these deficits are a crucial factor in triggering a speculative attack, illustrate the fact that the CEE economies are operating on the knife's edge. Against the background of huge capital inflows to finance the current account deficits the CEE countries were well advised to maintain some transitional periods for restrictions on short-term portfolio flows (hot money) in the course of capital account liberalisation as demanded by the EU. Second, it is very important for the transition countries to maintain an adequate fiscal deficit level. Fiscal surpluses are almost out reach for the transition countries because of the public expenditures to finance investments required to fullfil EU-obligations prior to accession. A relatively high fiscal deficit could easily tilt the market sentiment against the domestic currency if the economy is already in precarious conditions. And third, the exchange rate policy is the key to avoid a financial crisis. Against the background of persistent current account deficits in the Central and East European transformation countries and the importance of overvalued exchange rates as a driving force in the build up of crisis potential, the EU-accession countries are well advised to make their exchange rate systems more flexible. This would avoid an excessively high real appreciation of the real exchange rate. At the same time it would maintain the competitiveness of domestic enterprises on international markets and the export earnings would enable the central bank to keep an adequate level of foreign exchange reserves. However, introducing more flexibility into the exchange rate system of the Central and Eastern European countries and maintaining it for a sufficiently long time seems to be a daunting task as the new EU member states have to peg eventually the exchange rate irrevocably to the Euro. Therefore, it is all the more important that the EU-accession candidates pick the right exchange rate when entering the exchange rate mechanism of the European Monetary Union (ERM-II) and begin to reduce their current account deficits like Hungary and Poland have done so since 1999.

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Appendix

Overview of the variables used in the estimation:

a) Budget Balance

$$\frac{Budget\ Balance}{GDP_t} * 100$$

A budget deficit is has a (-) sign. The quarterly data for GDP are linearly interpolated to get monthly data. Source: WIIW.

b) GDP

$$\left[\frac{GDP_t}{GDP_{t-12}} - 1\right] * 100$$

GDP is defined as the annual change in GDP. The quarterly data for GDP are linearly interpolated to get monthly data. Source: WIIW.

c) Balance of the Current Account / GDP

$$\frac{Current\ Account_t}{GDP_t} * 100$$

A current account deficit is has a (-) sign. The quarterly data for the CA are linearly interpolated to get monthly data. Both current account balance and GDP are calculated as a 4-months moving average. Source: WIIW.

d) Industrial Production

$$\left[\frac{Industrial\ Production_t}{Industrial\ Production_{t-12}} - 1\right] * 100$$

Industrial production is defined as the annual change in industrial production.
Source: WIIW.

e) Exports

$$\left[\frac{Exports_t}{Exports_{t-12}} - 1\right] * 100$$

Exports are defined as the annual change in real exports in local currency. Exports are deflated with the CPI index. Source: WIIW.

f) Imports

$$\left[\frac{Imports_t}{Imports_{t-12}} - 1\right] * 100$$

Imports are defined as the annual change in imports in local currency. Source: WIIW.

g) Real Exchange Rate

$$REXR_t - \text{ linear } trend(REXR)$$

An overvaluation of the real exchange rate is defined as a negative deviation of the real exchange from its long term linear trend. Conversely, a positive deviation from the linear trend points to an undervaluation. Source: WIIW.

h) Bank Deposits

$$\left[\frac{Bank\ Deposits_t \ / \ GDP_t}{Bank\ Deposits_{t-12} \ / \ GDP_{t-12}} - 1\right] * 100$$

Bank deposits are defined as the annual change in the ratio of bank deposits to GDP. Source: WIIW.

i) Currency Reserves

$$\frac{Currency\ Reserves_t}{GDP_t} * 100$$

Currency reserves are defined as the ratio of currency reserves to GDP. Source: WIIW.

j) M2 / Currency Reserves

$$\left[\frac{M2_t \ / \ Reserves_t}{M2_{t-12} \ / \ Reserves_{t-12}} - 1\right] * 100$$

M2 to currency reserves is defined as the annual change in the ratio of M2 to currency reserves. Source: WIIW.

k) M2 Multiplier

$$\left[\frac{M2_t \ / \ Money\ base_t}{M2_{t-12} \ / \ Money\ base_{t-12}} - 1\right] * 100$$

The M2 multiplier is defined as the annual change in the ratio of M2 to the money base. Source: WIIW.

l) Domestic Credit

$$\left[\frac{Domestic\ Credit_t \ / \ GDP_t}{Domestic\ Credit_{t-12} \ / \ GDP_{t-12}} - 1\right] * 100$$

Domestic credit is defined as the annual change in the domestic Credit-to-GDP-ratio. Source: WIIW.

m) Interest Rate Differential

$$\textit{Domestic Interest Rate}_t \text{ ./. } \textit{US-Interest Rate}_t$$

The interest rate differential is defined as the difference between the domestic interest rate, usually the lending rate, and the yield of 7-Year US-Treasury bonds with constant maturity.
Source: WIIW and Federal Reserve Economic Database (FRED).

n) World Interest Rate

$$\textit{US-Interest Rate}_t$$

The US interest rate is used as a proxy for the world interest rate. The yield of 7-Year treasury bonds with constant maturity is chosen as the US interest rate.
Source: Federal Reserve Economic Database (FRED).

o) Foreign Debt

$$\left[\frac{\textit{Foreign Debt}_t \,/\, GDP_t}{\textit{Foreign Debt}_{t-12} \,/\, GDP_{t-12}} - 1\right] * 100$$

Foreign debt is defined as total consolidated foreign claims of BIS-reporting banks on individual countries. The quarterly data are linearly interpolated to obtain monthly data.
Source: BIS, Quarterly Review: International Banking and Financial Market Developments.

p) Short term Foreign Debt / Foreign Debt

$$\left[\frac{\textit{Short term Foreign Debt}_t \,/\, \textit{Foreign Debt}_t}{\textit{Short term Foreign Debt}_{t-12} \,/\, \textit{Foreign Debt}_{t-12}} - 1\right] * 100$$

Short term foreign debt is defined as claims of BIS-reporting banks on individual countries with a maturity of up to 1 year. The quarterly data are linearly interpolated to obtain monthly data.
Source: BIS, Quarterly Review: International Banking and Financial Market Developments.

q) Capital Flight

$$\left[\frac{\textit{Deposits}_t}{\textit{Deposits}_{t-12}} - 1\right] * 100$$

The deposits by the non-bank private sector with foreign BIS-reporting banks are used as a proxy for capital flight.
Source: BIS, Quarterly Review: International Banking and Financial Market Developments.

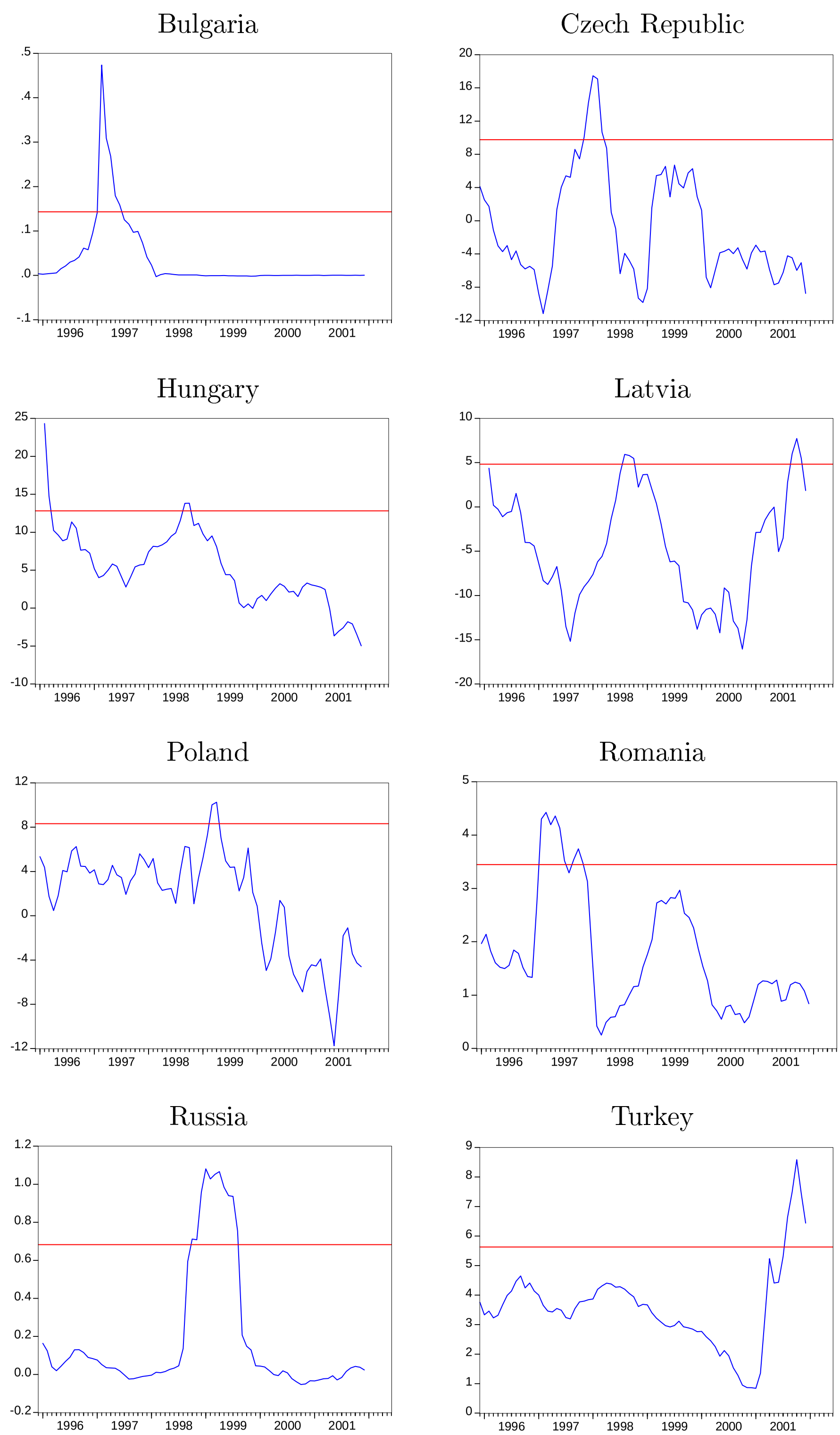
r) Credit Rating

The Credit Rating is defined as the Long Term Outlook of foreign currency credit rating of sovereign issuers. The credit rating is transformed into whole numbers ranging from 1 to 58 where 1 corresponds to AAA/stable and 58 to CC/stable, respectively.
Source: Standard & Poor's, Sovereign Ratings History Since 1975.

s) Presidential Elections

Presidential Election are interpreted as nation-wide elections; either presidential or parliamentary elections. The election dummy is equal to 1 for the election month and and the following eleven months and zero otherwise.
Source: International Foundation for Election Systems (IFES).

Figure 1: Exchange Market Pressure Index for Selected CEE Countries (Subset)



Note: The shaded areas mark the 18-months window before a crisis.

Source: Based on own calculations.

Table 2: Estimates of the Logit Models

	Logit		Rare Event Logit	
Variable	Coefficient	z statistic	Coefficient	z statistic
Current Account / GDP	-0.235	-4.75	-0.229	-4.83
Currency Reserves	-0.049	-2.37	-0.048	-1.99
Real Exchange Rate	-0.035	-2.59	-0.034	-2.09
Budget Deficit / GDP	-0.131	-2.64	-0.131	-2.79
Exports	-0.009	-1.62	-0.009	-2.12
Constant	-2.093	-5.34	-2.058	-4.86
Sample Size	710		710	
Pseudo R^2	0.097		0.099	

Note: All coefficients are significant at the 5 % level except for Exports in the ordinary logit model. The coefficient of Exports is significant at the 12 % level.

Source: Own calulations.

Table 3: Goodness of Fit of the Rare Event Logit Model

	In-sample*	**Out-of-sample****
Goodness of Fit		
Quadratic Probability Score (QPS)	0.202	0.169
Log Probability Score (LPS)	0.341	0.305
Global Squared Bias (GSB)	0.000014	0.0051
Cutoff Probability at 10 %		
Percent of observations correctly called	58.9	46.3
Percent of crises correctly called[a]	77.5	88.9
Percent of tranquil periods correctly called[b]	56.3	42.3
False alarms as a percent of total alarms[c]	79.5	87.5
Cutoff Probability at 20 %		
Percent of observations correctly called	81.6	79.0
Percent of crises correctly called[a]	42.7	16.7
Percent of tranquil periods correctly called[b]	87.1	81.7
False alarms as a percent of total alarms[c]	66.4	90.6
Memorandum		
Unconditional probability of a crisis (%)	12.92	9.26

* In-sample countries: BU, CZ, HU, LV, LI, PL, RO, RU, SL, TR.
** Out-of-sample countries: ES, HR, SV.

[a] A crisis period is correctly called when the estimated probability is above the cutoff probability and a crisis occurs within 12 months.

[b] A tranquil period is correctly called when the estimated probability is below the cutoff probability and no crisis occurs within 12 months.

[c] A false alarm is an observation with an the estimated probability of crisis above the cutoff probability and no crisis occurs within 12 months.

Source: Own calculations, Table adapted from Berg/Patillo (1999b).

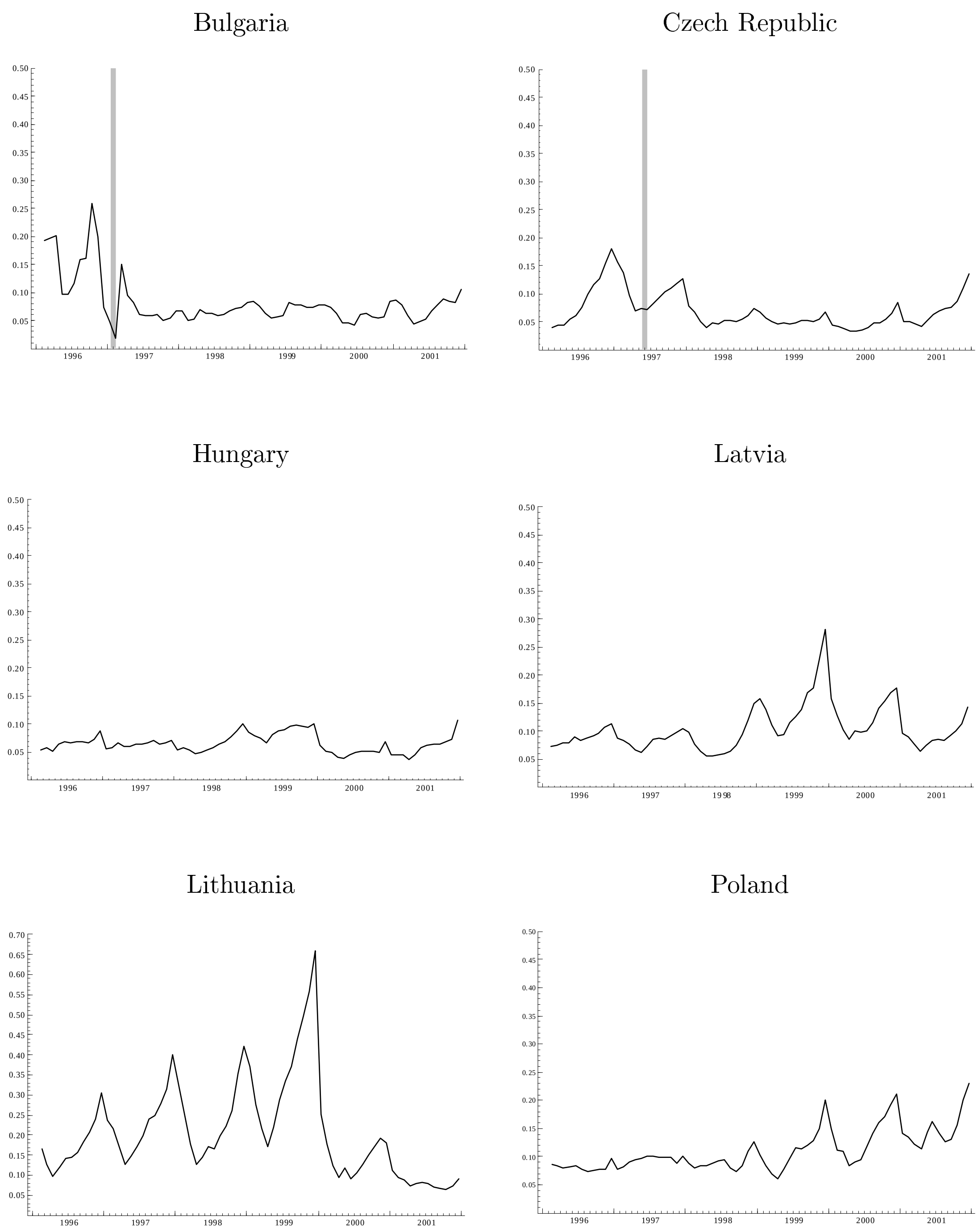
Table 4: χ^2 test of independence

Threshold	**20 %**	**25 %**	**30 %**	**35 %**
In sample	54.9*	51.3*	15.4*	4.2*
Out-of-sample	109.3*	105.0*	103.6*	100.7*

Note: The χ^2test statistic is asymptotic normally distributed. The null hypothesis is, that the forecasts and the actual outcomes are independent.
*means, that the null hypothesis is rejected at the 5% significance level. The critical value for $\chi^2_{0.05}(1)$ is 3.841.

Source: Own calulations.

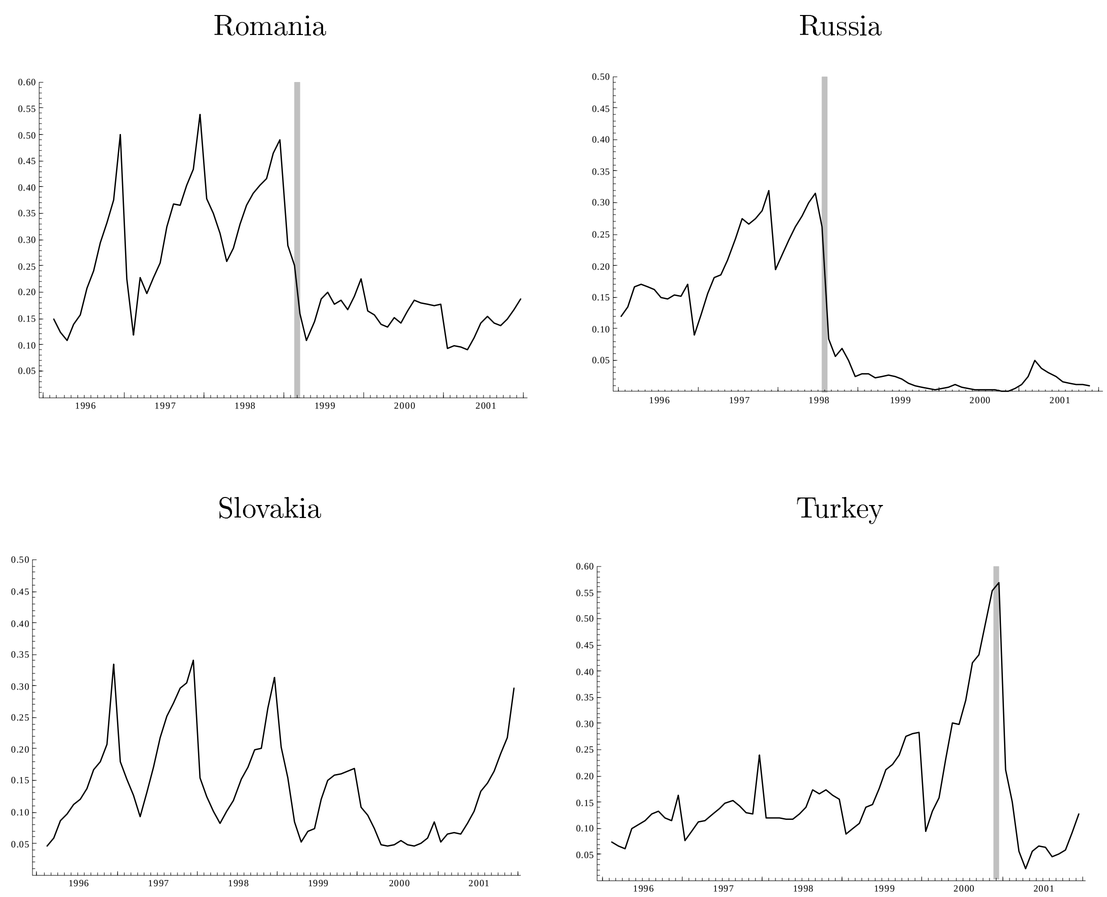
Figure 2: Estimated Probabilities of a Crisis (in-sample)



Note: The shaded areas mark the crisis month.

Source: Based on own calculations.

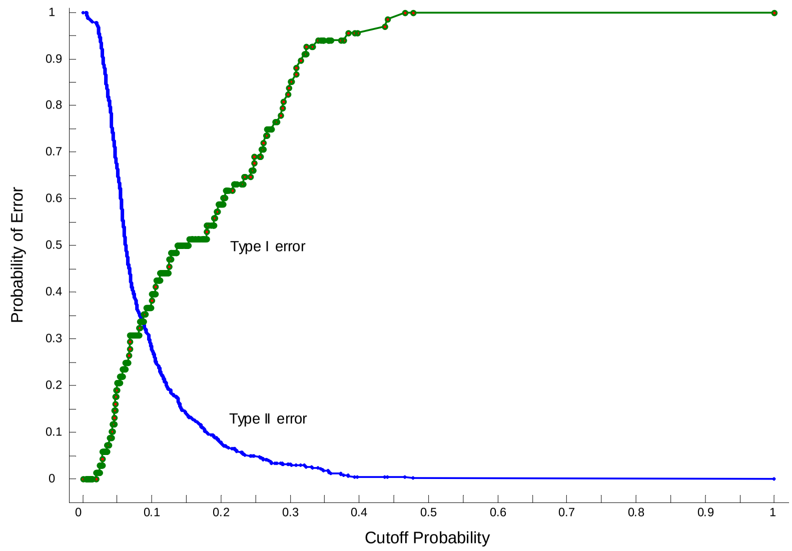
Figure 2: cont.



Note: The shaded areas mark the crisis month.

Source: Based on own calculations.

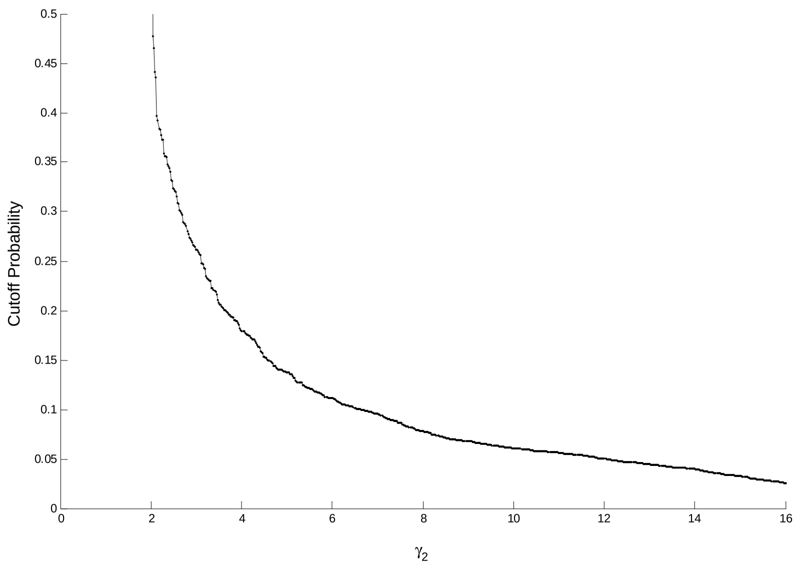
Figure 3: Prognostic Quality of the Model (in sample)



Note: A Type I error is committed if there was a crisis conditional on no alarm occurring, i.e. $\Pr[crisis \mid no\ alarm]$. This is equal to (1 - percent of tranquil periods correctly called). By the same token a Type II error is committed if there was not a crisis conditional on an alarm occurring, i.e. $\Pr[no\ crisis \mid alarm]$. This is equal to(1 - percent of crisis periods correctly called).

Source: Own calulations.

Figure 4: Choosing the Optimal Cutoff Probability



Note: The optimal threshold is calculated for $c_1 = 1$, $\gamma_1 = 2$, and $\gamma_2 > 2$. γ_2 measures the cost of the worst case scenario relative to cost of taking precautionary measures.

Source: Own calulations.

The Policy Maker's Loss function

The Loss function of the policy maker is defined as

$$L = (1-\omega)T_2(\tau) + \gamma_1\omega(1-T_1(\tau)) + \gamma_2\omega T_1(\tau), \tag{16}$$

where ω is the unconditional probability of a crisis and γ_1 and γ_2 are weights with $\gamma_1 > \gamma_2$. T_1 and T_2 are the Type I and Type II error, respectively. The probability of both types of errors depend on the threshold τ.

To show that

$$\left.\frac{d\tau}{d\omega}\right|_{dL=0} = -\frac{\partial L/\partial\omega}{\partial L/\partial\tau} < 0 \tag{17}$$

both partial derivatives must have equal signs.

$$\frac{\partial L}{\partial\omega} = \gamma_1(1-T_1) - T_2 + \gamma_2 T_1, \tag{18}$$

where the first term is positive while the sum of the last two terms is at least positive to the right of the intersection of the functions $T_1(\tau)$ and $T_2(\tau)$.

$$\frac{\partial L}{\partial\tau} = T_2'(1-\omega) - \omega T_1'(\gamma_1-\gamma_2) \tag{19}$$

The first term is negative because $T_2' < 0$ and the second term is also negative because $T_1' > 0$ and $\gamma_2 > \gamma_1$. For $\partial L/\partial\tau > 0$ it is necessary that

$$T_2'(1-\omega) < \omega T_1'(\gamma_1-\gamma_2). \tag{20}$$

Assuming that $-T_2'=T_1'$ the following must hold

$$-\frac{1-\omega}{\omega} < \gamma_1 - \gamma_2, \tag{21}$$

which is only the case if γ_2 is not too large. Or more specifically, the smaller ω the larger can be γ_2 for the condition to hold.

Analogously, it is easy to show that

$$\left.\frac{d\tau}{d\gamma_2}\right|_{dL=0} = -\frac{\partial L/\partial\gamma_2}{\partial L/\partial\tau} < 0. \tag{22}$$

Since

$$\frac{\partial L}{\partial \gamma_2} = \tau \omega T_1 > 0, \tag{23}$$

$\partial L/\partial \tau$ must be positive which was demonstrated above.